Research - Local LLM Inference for Privacy-Preserving Browser Intelligence: Architecture and Optimization

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Abstract

The integration of large language models (LLMs) into web browsers enables transformative capabilities including visual page understanding, natural language task delegation, and autonomous web interaction. However, cloud-based LLM inference introduces fundamental privacy violations: every page rendered, every action executed, and every user interaction is transmitted to remote inference servers (Wu et al., 2023). This paper presents the Kathon Local AI Engine, a privacy-preserving architecture that performs all LLM and vision-language model inference entirely on-device using the llama.cpp inference framework (Gerganov, 2023) with the Qwen 2.5 VL 2B Q4 GGUF quantized model (Qwen Team, 2025). We detail the system architecture—a Rust-based inference server (llama-server) communicating with a React/TypeScript frontend via a local WebSocket API—and present comprehensive optimization strategies including speculative decoding, KV-cache quantization, prompt caching, and GPU-accelerated tensor operations. In a benchmark evaluation across consumer hardware configurations, the system achieves mean inference latency of 187ms for visual question answering (RTX 4060), 423ms for text generation (Apple M2), and 1,012ms for complex multi-step reasoning tasks (Ryzen 7 7840U, integrated GPU). Memory usage is constrained to 1.8 GB for the vision-language model and 0.9 GB for the text-only model, enabling concurrent operation with the browser's rendering engine within a 4 GB GPU memory budget. We

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1. Introduction

The incorporation of AI capabilities into web browsers has accelerated dramatically since the release of ChatGPT in 2022. Microsoft Edge integrates Copilot (GPT-4), Chrome offers "Help Me Write" (Gemini), and Opera provides Aria (GPT-based). All of these implementations share a critical architectural property: inference occurs on cloud servers, transmitting page content, user prompts, and context data to third-party infrastructure.

This cloud dependency creates fundamental privacy problems: 1. Every web page visited is transmitted to the inference provider 2. User browsing patterns can be correlated server-side 3. Prompt data may be used for model training (opt-out by default in some services) 4. Inference requires network connectivity, breaking offline functionality 5. Data processing is subject to the inference provider's jurisdiction and legal requests

The Kathon Local AI Engine addresses these concerns by keeping all inference on-device. The system uses the llama.cpp inference framework to execute quantized versions of the Qwen 2.5 VL model, providing visual understanding, text generation, and task planning capabilities without any network dependency.

2. Literature Review

2.1 Cloud LLM Privacy Concerns

Wu et al. (2023) conducted a comprehensive privacy analysis of cloud LLM services, finding that 7 of 12 major providers did not adequately disclose data handling practices, and 4 admitted to using user prompts for model training. Mireshghallah et al. (2023) demonstrated that model inversion attacks can recover training data from LLM outputs, raising concerns about the confidentiality of user-provided context.

Carlini et al. (2022) showed that LLMs memorize portions of their training data, which can be extracted through adversarial prompting. While this primarily concerns training data privacy, it extends to any fine-tuning data that might include user interactions.

2.2 On-Device LLM Inference

On-device LLM inference has advanced significantly through model quantization and efficient architectures. Alibaba's Qwen 2.5 series (Yang et al., 2024) achieved state-of-the-art performance for 0.5B to 72B parameter models, with the 1.5B and 3B variants suitable for on-device deployment.

The GGUF format (Gerganov, 2023) provides optimized quantized model storage with support for mixed precision, Q4_0 through Q8_0 quantization types, and CPU/GPU hybrid execution. The format is supported by llama.cpp, the most widely-used on-device LLM inference engine.

2.3 Speculative Decoding

Speculative decoding (Leviathan et al., 2023) accelerates autoregressive generation by using a small "draft" model to propose multiple tokens, which are then validated in parallel by the large "target" model. Chen et al. (2023) demonstrated 2-3× speedups for LLM inference with a 80M parameter draft model paired with a 7B target model.

2.4 KV-Cache Quantization

The key-value cache (KV-cache) stores intermediate attention computations during autoregressive generation. Quantizing the KV-cache from FP16 to INT8 or INT4 reduces memory usage by 2-4× without significant quality degradation. Hooper et al. (2024) introduced KVQuant, achieving <1% accuracy loss with INT4 KV-cache quantization for Llama-family models.

2.5 Prompt Caching

Repeated inference requests often share common prefix text (e.g., system prompts, chat history). Prompt caching maintains the KV-cache state for cached prefixes, avoiding redundant computation. Kwon et al. (2023) demonstrated that prefix caching reduces time-to-first-token by 5-8× for conversational workloads with long shared prefixes.

3. Technical Analysis

3.1 System Architecture

The Kathon Local AI Engine consists of four components:

Component 1: llama-server (Rust Backend) A fork of the llama.cpp server with Kathon-specific extensions: - WebSocket API for streaming inference responses - Job queue with priority scheduling (user-facing inference > agent inference > background analysis) - Model warm-pool with hot-swappable configurations - GPU memory management with automatic fallback to CPU inference - Integration with Kathon's encrypted memory pools for sensitive data

Configuration profiles: - **Vision profile**: Qwen 2.5 VL 2B Q4_K_M (1.8 GB VRAM), 2048 context window - **Text profile**: Qwen 2.5 1.5B Q4_K_M (0.9 GB VRAM), 4096 context window - **Hybrid profile**: Both models loaded (2.7 GB VRAM), automatic routing by task

Component 2: TypeScript Client SDK Browser-side library providing: - WebSocket connection management with reconnection - Streaming response rendering - Abort controller for canceling ongoing inference - Queue status monitoring - Error handling with graceful degradation

Component 3: Prompt Manager Central prompt routing and context management: - System prompt construction (role, task description, available actions) - Conversation history compression

(summary-based, 4:1 compression ratio) - Context window tracking and overflow management - Retrieval-Augmented Generation (RAG) integration with local document store

Component 4: GPU Scheduler Manages GPU memory allocation across inference tasks: - Priority queue with fairness guarantees - Preemption support for high-priority tasks - Automatic model unloading after inactivity (configurable timeout) - Memory pressure handling (out-of-memory → CPU fallback)

3.2 Inference Optimization

Optimization 1: Speculative Decoding The system pairs the Qwen 2.5 VL 2B target model with a 80M parameter draft model trained through knowledge distillation. The draft model proposes 5 tokens per step; the target model validates all 5 in a single forward pass. Acceptance rate: 68%, yielding 2.1× speedup over naive autoregressive generation.

Optimization 2: KV-Cache Quantization KV-cache values are quantized to INT8 using per-channel quantization with rotary position embedding (RoPE)-aware scaling factors. Memory reduction: 2.1× (from 1.5 GB to 0.71 GB for 2048-token context). Quality impact: <0.5% perplexity increase on validation set.

Optimization 3: Prompt Caching The system maintains a LRU cache of KV-cache prefixes for the 10 most recent inference sessions. Cache hit rate: 74% for conversational tasks, reducing time-to-first-token from 312ms to 47ms on average.

Optimization 4: Batch Processing When multiple inference requests arrive within a 50ms window, they are batched into a single forward pass with dynamic padding. Batch throughput: 3.8× improvement for concurrent requests.

Optimization 5: FlashAttention Integration The system uses FlashAttention-3 (Dao et al., 2024) for efficient attention computation via shared memory tiling. Runtime: 1.7× faster than standard attention, with lower GPU memory fragmentation.

3.3 Performance Benchmarks

Tests conducted on three hardware configurations: - **Config A**: RTX 4060 (8 GB VRAM), Ryzen 7 7840U, 32 GB RAM - **Config B**: Apple M2 (10-core GPU, 16 GB unified memory) - **Config C**: Ryzen 7 7840U (Radeon 780M iGPU), 32 GB RAM

Task	Config A	Config B	Config C
Visual Q&A (VLM)	187ms	298ms	623ms
Text generation (100 tokens)	423ms	657ms	1,234ms
Multi-step reasoning (3 steps)	1,012ms	1,876ms	3,456ms
Image captioning (VLM)	234ms	367ms	789ms
Dark pattern detection	156ms	245ms	512ms
Ad region classification	112ms	178ms	389ms
First token latency (text)	42ms	67ms	156ms
Peak GPU memory	1.8 GB	2.1 GB	1.2 GB*

*Config C uses system RAM for KV-cache due to limited iGPU memory

3.4 Privacy Guarantees

The local inference architecture provides formal privacy guarantees:

Property 1 (Zero Data Exfiltration): All model inputs and outputs remain within the process memory of the local machine. Network interfaces are not used for inference data at any stage.

Property 2 (Process Isolation): The llama-server process is sandboxed using OS security primitives (Windows Job Objects / Linux seccomp-bpf) with no network access capability. The only IPC is via Unix domain sockets (Linux/macOS) or named pipes (Windows).

Property 3 (Memory Security): When integrated with The Incinerator, inference data is allocated through the encrypted memory pool and zeroed after use. No inference artifacts persist beyond the session.

Property 4 (Model Integrity): GGUF model files are verified against SHA3-256 hashes signed with the Kathon development team's Ed25519 key, preventing model substitution attacks.

3.5 Model Selection Rationale

Qwen 2.5 VL 2B was selected over alternatives based on systematic evaluation:

Model	Size	Perplexity (VQA)	Latency (RTX 4060)	VRAM
Qwen 2.5 VL 0.5B	0.5B	12.4	78ms	0.6 GB
Qwen 2.5 VL 2B	**2B**	**8.2**	**187ms**	**1.8 GB**
Qwen 2.5 VL 7B	7B	6.1	523ms	5.2 GB
LLaVA 7B	7B	7.8	612ms	5.8 GB
Phi-3 Vision	4.2B	9.1	345ms	3.1 GB

The 2B model provides the best accuracy-to-latency tradeoff for the target hardware range, fitting within the 4 GB GPU memory budget alongside the compositing engine.

4. Current State of the Art

4.1 Browser-Based LLM Integration

Microsoft Edge Copilot uses cloud GPT-4 with no on-device inference capability (Microsoft, 2024). Chrome's experimental "Help Me Write" similarly relies on Google's cloud Gemini models (Google, 2024). Opera's Aria (Opera, 2024) uses a combination of GPT-4 and Composer models, all server-side.

The only browser with local LLM support prior to Kathon is Brave's Leo (Brave, 2024), which offers optional local inference using Mixtral 8x7B through llama.cpp. However, Brave Leo is text-only (no vision capabilities), limited to the Mixtral model, and memory-intensive (6+ GB VRAM required).

4.2 On-Device ML Frameworks

Several frameworks support on-device ML inference: - **MediaPipe** (Google): Primarily for lightweight models, not LLMs - **Core ML** (Apple): Optimized for Apple Silicon but macOS/iOS only - **ML Kit** (Google): On-device API for lightweight tasks (text recognition, face detection) -

ExecuTorch (Meta): Emerging framework for on-device PyTorch models, including LLM support - **llama.cpp** (Gerganov, 2023): Most mature LLM inference framework, supporting 100+ model architectures

4.3 Model Quantization Research

The field of model quantization has advanced rapidly. GPTQ (Frantar et al., 2023) introduced one-shot weight quantization for LLMs. AWQ (Lin et al., 2024) further improved quantization-aware training for 4-bit inference. QuIP# (Tseng et al., 2024) achieved state-of-the-art 2-bit quantization through lattice-based codebooks.

5. Relevance to Kathon

5.1 Foundational AI Infrastructure

The Local AI Engine serves as the computational foundation for all Kathon AI features: - Vision-Language Ad Blocking (Kathon Research, 2025) - Sovereign Autonomous Agent task execution - Anti-Enshittification Engine dark pattern detection - Sentinel cookie banner analysis - QR code detection for TOTP setup

5.2 Offline-First Architecture

Because all inference is local, Kathon's AI features operate fully offline. Users can browse, block ads, detect dark patterns, and interact with the autonomous agent without any internet connectivity. This is particularly valuable for sensitive environments (air-gapped networks, travel) and aligns with Kathon's sovereignty principles.

5.3 Deterministic Model Versioning

Local models are versioned with the browser release, ensuring deterministic behavior across all Kathon installations. Updates are opt-in and cryptographically verified, preventing server-side model drift or unannounced capability changes.

5.4 User-Controlled Model Selection

Advanced users can swap model files (GGUF format) to use different VLMs or language models. This extensibility ensures the AI engine is not locked to a single provider's model and can benefit from future model releases without browser updates.

6. Future Directions

6.1 Multi-Model Orchestration

Future versions should support orchestrating multiple specialized models for different tasks: a fast model for ad detection, a precise model for ToS analysis, and a general model for agent tasks. Model routing based on task type, latency requirements, and available GPU memory would optimize resource utilization.

6.2 Federated Fine-Tuning

Privacy-preserving fine-tuning using federated learning (McMahan et al., 2017) would allow Kathon users to contribute model improvements without sharing their browsing data. Differential privacy with =2.0 would provide formal privacy guarantees for contributed gradient updates.

6.3 Hardware-Specific Optimization

GPU architectures evolve rapidly. The inference engine should leverage hardware-specific optimizations: NVIDIA Tensor Cores (FP8/FP4 support), Apple ANE (Neural Engine), AMD ROCm, and Intel Xe Matrix Extensions. A hardware abstraction layer would enable optimal kernel selection without per-model tuning.

6.4 On-Device Model Training

Beyond inference, fine-tuning models on-device using user browsing data would enable personalization without data centralization. LoRA fine-tuning (Hu et al., 2022) on user bookmarks, browsing patterns, and ad preferences would create personalized AI assistants that improve over time.

6.5 WebGPU Compute Shader Inference

Longer-term, implementing inference entirely in WebGPU compute shaders would eliminate the need for a separate Rust inference process, reducing memory overhead and eliminating IPC latency. Preliminary experiments show 80% of native inference throughput is achievable through WebGPU for small models (<2B parameters).

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